

(19)

Europäisches Patentamt

European Patent Office

Office européen des brevets



(11)

EP 0 844 582 A2

(12)

## EUROPEAN PATENT APPLICATION

(43) Date of publication:  
27.05.1998 Bulletin 1998/22

(51) Int Cl. 6: G06K 9/00

(21) Application number: 97309444.4

(22) Date of filing: 24.11.1997

(84) Designated Contracting States:  
AT BE CH DE DK ES FI FR GB GR IE IT LI LU MC  
NL PT SE  
Designated Extension States:  
AL LT LV MK RO SI

(30) Priority: 26.11.1996 US 31816 P  
21.05.1997 US 859902

(71) Applicant: NCR INTERNATIONAL INC.  
Dayton, Ohio 45479 (US)

(72) Inventors:  

- Khosravi, Mehdi  
Roswell, Georgia 30075 (US)
- Hayes, Monson Henry, III  
Marietta, Georgia 30068 (US)
- Nefian, Ara Victor  
Atlanta, Georgia 30319 (US)

(74) Representative: Irish, Vivien Elizabeth et al  
International IP Department,  
NCR Limited,  
206 Marylebone Road  
London NW1 6LY (GB)

## (54) System and method for detecting a human face

(57) The present invention relates to a system for the processing of video images which include human faces. The invention is applicable to a system in which the images are generated by a video camera and stored in a storage means ready to be processed.

The system for processing the images include component analysis means (212,213) to analyse the pixels of the image to identify a region of connected components in the foreground of the image. An ellipse fitting means (503,504,505,506,507) performs an iterative ellipse fitting algorithm to fit one or more vertical ellipses

to the connected components in the identified region, each ellipse representing a possible human face. In order to distinguish between occluded human figures, a plurality of possible models of borders are presented to separate individual faces in the identified region. Probability computing means (403) perform a computation of the probability of each model based on the ellipse or ellipses fitted in the identified region. The parameters of each model are iteratively adjusted to maximise the probability computation for that model and a selection is made of the model having the highest probability.

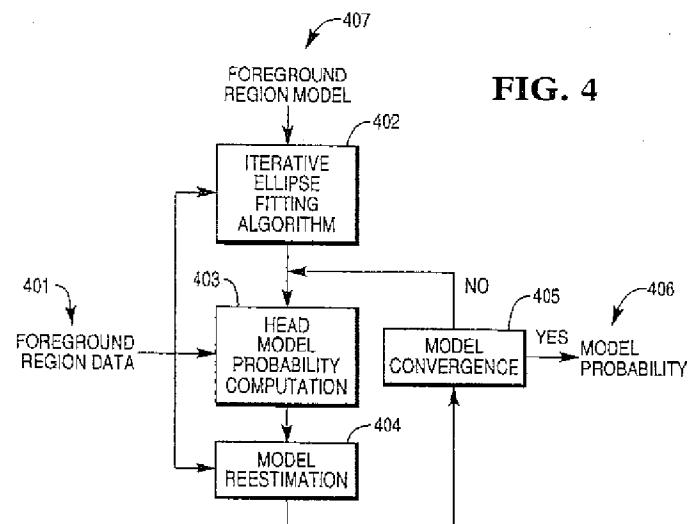


FIG. 4

**Description**

The present invention generally relates to real-time video image analysis, and more specifically to the detection of human faces and eyes within real-time video images.

In recent years, the detection of human faces from video data has become a popular research topic. There are numerous commercial applications of face detection, such as in face recognition, verification, classification, identification as well as security access and multimedia. To extract the human face in an uncontrolled environment, most prior art techniques attempt to overcome the difficulty of dealing with issues such as variations in lighting, variations in pose, occlusion of people by other people, and cluttered or non-uniform backgrounds.

In one prior art face detection technique, an example-based learning approach for locating unoccluded human frontal faces is used. The approach measures a distance between the local image and a few view-based "face" and "non face" pattern prototypes at each image location to locate the face. In another technique, the distance to a "face space", defined by "eigenfaces", is used to locate and track frontal human faces. In yet another prior art technique, human faces are detected by searching for significant facial features at each location in the image. Finally, in other techniques, a deformable template based approach is used to detect faces and to extract facial features.

In addition to the detection of faces within video image sequences, prior art systems have attempted to detect eyes on human heads. For example, Challepa et al., "Human and Machine Recognition of Faces: A Survey", Proceedings of the IEEE, vol. 83, no. 5, pp. 705-740, May 1995, described a process for detecting eyes on a human head, where the video image includes a front view of the head. For frontal views, eye detection that is based on geometrical measures has been extensively studied, by, for example, Stringa, "Eyes Detection for Face Recognition", Applied Artificial Intelligence, vol. 7, no. 4, pp. 365-382, Oct.-Dec. 1993 and Brunelli et al., "Face Recognition: Features versus Templates", IEEE Transaction on Pattern Analysis and Machine Intelligence, October 1993. Additionally, Yuilee et al., "Feature Extraction from Faces Using Deformable Templates", International Journal of Computer Vision, vol. 8, pp. 299-311, 1992, describe a deformable template-based approach to facial feature detection. However, these methods may lead to significant problems in the analysis of profile or back views. Moreover, the underlying assumption of dealing only with frontal faces is simply not valid for real-world applications.

There is therefore a significant need in the art for a system that can quickly, reliably and flexibly detect the existence of a face or faces within a video-image, and that can also extract various features of each face, such as eyes.

According to the invention a system for processing a video image comprising pixels representing a foreground including one or more human faces, the system comprising;

component analysis means to process the pixels of the image to identify a region of connected components in the foreground of the image.

ellipse fitting means to perform an iterative ellipse fitting algorithm to fit one or more ellipses to the connected components in the identified region.

means to provide a model of borders for one or more separate individual faces in the identified region,

probability computing means to perform a computation of the probability of the model based on the ellipse or ellipses fitted in the identified region, and means to iteratively adjust the model to maximise the probability computation.

The invention will now be described by way of example only with reference to the accompanying drawings:-

FIG. 1 is a block diagram of the present invention.

FIG. 2 is a flow diagram depicting the overall operation of the present invention.

FIG. 3 is a flow diagram depicting a process for choosing the most likely model of people within the video image.

FIG. 4 is a flow diagram further depicting the modeling process of FIG. 3.

FIG. 5 is a flow diagram depicting a process for fitting an ellipse around the head of a person detected within a video image.

FIGS. 6A-6D, 7A-7C, 8A-8D and 9A-9D depict examples of video images that may be processed by the present invention.

FIG. 10 depicts criteria that may be used to model a face within a video-image.

Figs. 11-12 are flow-diagrams depicting processes that are performed by the present invention.

## 1. The Video System

FIG. 1 depicts the overall structure of the present invention in one embodiment. The hardware components of the present invention may consist of standard off-the-shelf components. The primary components in the system are one or more video cameras 110, one or more frame grabbers 120, and a processing system 130, such as a personal computer (PC). The combination of the PC 130 and frame grabber 120 may collectively be referred to as a "video

processor" 140. The video processor 140 receives a standard video signal format 115, such as RS-170, NTSC, CCIR, PAL, from one or more of the cameras 110, which can be monochrome or color. In a preferred embodiment, the camera (s) 110 may be mounted or positioned to view a selected area of interest, such as within a retail establishment or other suitable location.

5 The video signal 115 is input to the frame grabber 120. In one embodiment, the frame grabber 120 may comprise a Meteor Color Frame Grabber, available from Matrox. The frame grabber 120 operates to convert the analog video signal 115 into a digital image stored within the memory 135, which can be processed by the video processor 140. For example, in one implementation, the frame grabber 120 may convert the video signal 115 into a 640 x 480 (NTSC) or 768 x 576 (PAL) color image. The color image may consist of three color planes, commonly referred to as YUV or YIQ. 10 Each pixel in a color plane may have 8 bits of resolution, which is sufficient for most purposes. Of course, a variety of other digital image formats and resolutions may be used as well, as will be recognized by one of ordinary skill.

15 As representations of the stream of digital images from the camera(s) 110 are sequentially stored in memory 135, analysis of the video image may begin. All analysis according to the teachings of the present invention may be performed by the processing system 130, but may also be performed by any other suitable means. Such analysis is described in further detail below.

## 2. Overall Process Performed by the Invention

20 An overall flow diagram depicting the process performed by the processing system 130 of the present invention is shown in FIG. 2. The first overall stage 201 performed by the processing system 130 is the detection of one or more human heads (or equivalent) within the video image from camera 110, which is stored in memory 135, and the second overall stage 202 is the detection of any eyes associated with the detected human head(s). The output 230 of stages 201-202 may be passed to recognition and classification systems (or the like) for further processing.

25 The steps performed in stage 201 are described below.

25 The first steps 212-213 and 216 (of the head detection stage 201) is the segmentation of people in the foreground regions of the sequence of video images stored in memory 135 over time, which is represented in FIG. 2 as video sequence 211. Such segmentation is accomplished by background modeling (step 216), background subtraction and thresholding (step 212) and connected component analysis (step 213). Assuming the original image 600 of FIG. 6A (which may be stored in memory 135, etc.), as shown in FIG. 6B, the result of steps 212 and 213 is a set of connected regions (blobs) (e.g., blobs 601) which have large deviations from the background image. The connected components 601 are then filtered also in step 213 to remove insignificant blobs due to shadow, noise and lighting variations, resulting in, for example, the blobs 602 in FIG. 6C.

30 To detect the head of people whose bodies are occluded, a model-based approach is used (steps 214-215, 217). In this approach, different foreground models (step 217) may be used for the case where there is one person in a foreground region and the case where there are two people in a foreground region. The output of step 214 are the probabilities of the input given each of the foreground region models. Step 215 selects the model that best describes the foreground region by selecting the maximum probability computed in step 214. An example output of step 215 is shown in Figure 6D, wherein the ellipse 603 is generated.

35 The functionality performed by system 130 of steps 214-215 and 217 is illustrated in FIGS. 9A-9D. Each of FIGS. 40 9A-9D represent a video image that may be created by frame grabber 120 and stored in memory 135 (FIG. 1). FIG. 9A depicts an example foreground region representing one person 901. The one person model (x1, x2) matches the input data. FIG. 9B depicts the same foreground region modeled as two persons (x1, x2, x3). In this case two dashed ellipses 911, 912 are fitted but they do not represent the correct location of the head 913. The probability of the foreground region is computed for each model as is described later and the system automatically selects the model for 45 one person to best describe the foreground region in this case.

45 FIGS. 9C and 9D depict an example foreground region with two people 902, 903 with occluded bodies. In this case, the system 130 of the present invention selects the two people model (x1, x2, x3) to best represent the data. When a single person model is used to describe the foreground region, the large dashed ellipse 921 is fitted which 50 does not correspond to any of the people's 902, 903 heads. The system does not select the single person model because the probability of one person model for the given input data is lower than the probability of the two person model given the input data.

55 The next overall stage 202 in the present invention is the detection of eyes from varying poses and the extraction of those faces that correspond to frontal views. In prior art articles, such as those described by Turk et al., "Face Recognition Using Eigenfaces", Proceedings on International Conference on Pattern Recognition, 1991 and Brunelli et al., "Face Recognition: Features versus Templates", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 15, no. 10, October 1993, techniques have been proposed whereby eyes are detected from frontal views. However, the assumption of frontal view faces is not valid for real world applications.

In the present invention, in steps 221-222 the most significant face features are detected by analyzing the con-

5 nected regions of large deviations from facial statistics. Region size and anthropological measure-based filtering detect the eyes and the frontal faces. Eye detection based upon anthropological measures for frontal views has been studied in the prior art (see, e.g., Brunelli et al., cited previously). However, such methods can run into problems in the analysis of profile or back views of faces. In step 223, filtering based on detected region size is able to remove big connected components corresponding to hair as well as small regions generated by noise or shadow effects. In step 224, the remaining components are filtered considering the anthropological features of human eyes for frontal views, and again the output 230 may be passed to another system for further processing. The eye detection stage 202 of the present invention is described in further detail below.

10 3. Segmentation of Foreground Regions

To extract moving objects within the video image stored in memory 135, the background may be modeled as a texture with the intensity of each point modeled by a Gaussian distribution with mean  $\mu$  and variance  $\sigma$ ,  $N_b(\mu, \sigma)$  (step 216). The pixels in the image are classified as foreground if  $P(O(x,y)|N_b(\mu, \sigma)) \leq T$  and as background if  $P(O(x,y)|N_b(\mu, \sigma)) > T$ . The observation  $O(x,y)$  represents the intensity of the pixels at location  $(x,y)$ , and  $T$  is a constant (step 212).

15 The connectivity analysis (step 213) of the "foreground" pixels generates connected sets of pixels, i.e. sets of pixels that are adjacent or touching. Each of the above sets of pixels describe a foreground region. Small foreground regions are assumed to be due to shadow, camera noise and lighting variations and are removed.

20 4. The Foreground Region Modeling System

The foreground regions are analyzed in further detail in steps 214-215 and 217 to detect the head. It is known that if there is only one head in the image, then it may be detected by finding the upper region in each set of connected foreground regions. However, this technique fails when people in an image are occluded by other people. In this case, a foreground region may correspond to two or more people, and finding the regions corresponding to heads requires a more complicated approach. In the case of partial people occlusion, in which bodies are occluded by other bodies, but heads are not occluded, special processing must be performed.

To determine the head positions in this case, the number of people in each foreground region must be determined. As shown in FIG. 3, in order to determine the number of people within the video image,  $N$  separate models  $\lambda_i$  (301), (where  $i$  may equal 1 to  $N$ ) may be built, each model  $\lambda_i$  301 corresponding to  $i$  people in a set of connected foreground region. Based on the assumption that faces are vertical and are not occluded, the model parameters for model  $\lambda_i$  are  $(x_0, x_1, \dots, x_i)$  where  $i$  is the number of people and  $x_k$  (where  $k=1$  to  $i$ ) specifies the horizontal coordinates of the vertical boundaries that separate the  $i$  head region in model  $\lambda_i$ . The approach used to determine the number of people in each foreground region is to select in step 215 the model  $\lambda_i$  301 for which the maximum likelihood is achieved:

35

$$\lambda = \arg \max_{i \in [1, N]} P(O(x, y) | \lambda_i) \quad (1)$$

40

where the observations  $O(x, y)$  are the pixel intensities at coordinates  $(x, y)$  in the foreground regions and  $P(O(x, y) | \lambda_i)$  is the likelihood functions for the  $i^{th}$  model 301.

45 The probability computation steps 302 in FIG. 3 determines the likelihood functions for each model 301. In step 215, the observations  $O(x, y)$  in the foreground regions are used to find for each model  $\lambda_i$  301 the optimal set of parameters  $(x_0, x_1, \dots, x_i)$  that maximize  $P(O(x, y) | \lambda_i)$ , i.e. to find the parameters  $(x_0, x_1, \dots, x_i)$  that "best" segment the foreground regions (step 215). It will be shown later that the computation of  $P(O(x, y) | \lambda_i)$  for each set of model parameters 301 requires an efficient head detection algorithm inside each rectangular window bordered by  $x_{j-1}$  and  $x_j$ ,  $j=1, \dots, i$ .

50 It is common to approximate the support of the human face by an ellipse. In addition, it has been determined that the ellipse aspect ratio of the human face is, for many situations, invariant to rotations in the image plane as well as rotations in depth. Based on the above, the head model 301 is parameterized by the set  $(x_0, y_0, a, b)$ , where  $x_0$  and  $y_0$  are the coordinates of the ellipse centroid and  $a$  and  $b$  are the axis of the ellipse. The set  $(x_0, y_0, a, b)$  is determined through an efficient ellipse fitting process described elsewhere with respect to FIG. 5.

55 5. Computation of Foreground Model Likelihood Functions

Based on the assumption that human faces are vertical and are not occluded, it is deemed appropriate to parameterize models  $\lambda_i$  301 over the set of parameters  $(x_0, x_1, \dots, x_i)$  which are the horizontal coordinates of the vertical borders

that separate individual faces in each foreground region. The set of parameters  $(x_0, x_1, \dots, x_i)$  is computed iteratively to maximize  $P(O(x, y) | \lambda_i)$ . In a Hidden Markov Model (HMM) implementation (described further in Rabiner et al., "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition", Proceedings of the IEEE, February 1989), this corresponds to the training phase in which the model parameters are optimized to best describe the observed data.

To define the likelihood functions  $P(O(x, y) | \lambda_i)$ , a preliminary discussion about the head detection process algorithm may be helpful. In the present invention, the head is determined by fitting an ellipse around the upper portions of the foreground regions inside each area bounded by  $x_{j-1}, x_j$ ,  $j = 1, \dots, i$ . The head detection problem is reduced to finding the set of parameters  $(x_0, y_0, a, b)$  that describe an ellipse type deformable template (step 402 in FIG. 4). Parameters  $x_0$  and  $y_0$  describe the ellipse centroid coordinates and  $a$  and  $b$  are the ellipse axis. The ellipse fitting algorithm is described in more detail with respect to FIG. 5.

For each set of parameters  $(x_0, y_0, a, b)$  a rectangular template (W in FIG. 10) is defined by the set of parameters  $(x_0, y_0, \alpha a, \alpha b)$ , where  $x_0$  and  $y_0$  are the coordinates of the center of the rectangle and  $\alpha a, \alpha b$  are the width and length of the rectangle, and  $\alpha$  is some constant (see FIG. 10). In each area bounded by  $x_{j-1}, x_j$ ,  $R_{out,j}$  is the set of pixels outside the ellipse template and inside the rectangle template and  $R_{in,j}$  is the set of pixels inside the ellipse template (FIG. 10). The regions  $R_{in,j}$  and  $R_{out,j}$  locally classify the image in "face" and "non face" regions. Based on the above discussion, the likelihood function  $P(O(x, y) | \lambda_i)$  for the model  $\lambda_i$  is determined by the ratio of the number of foreground pixels classified as "face" and background pixels classified as "non face" in each area bounded by  $x_{j-1}, x_j$  (where  $j = 1$  to  $i$ ), over the total number of pixels in "face" and "non face" regions (step 403). This is described in Equation (2) below.

$$P(O(x, y) | \lambda_i) = \frac{\sum_{j=1}^i \left( \sum_{(x, y) \in R_{in,j}} f(x, y) + \sum_{(x, y) \in R_{out,j}} b(x, y) \right)}{\sum_{j=1}^i \left( \sum_{(x, y) \in R_{out,j}} (h(x, y) + f(x, y)) + \sum_{(x, y) \in R_{in,j}} (f(x, y) + b(x, y)) \right)} \quad (2)$$

$$\text{where } b(x, y) = \begin{cases} 1, & \text{if } p(O(x, y) | N_b(\mu, \sigma)) > T \\ 0, & \text{otherwise} \end{cases}$$

(3)

$$\text{and } f(x, y) = \begin{cases} 1, & \text{if } p(O(x, y) | N_b(\mu, \sigma)) < T \\ 0, & \text{otherwise} \end{cases}$$

(4)

The goal in steps 301-302 is not only to compute the likelihood functions  $P(O(x, y) | \lambda_i)$  for a set of parameters  $(x_0, x_1, \dots, x_i)$ , but also to determine the set of parameters that maximize  $P(O(x, y) | \lambda_i)$ . The initial parameters  $(x_0, x_1, \dots, x_i)$  for model  $\lambda_i$  are chosen to uniformly segment the data, i.e.  $x_j - x_{j-1} = (x_i - x_0)/i$  (where  $j = 1$  to  $i$ ). As described in FIG. 4, the parameters  $(x_0, x_1, \dots, x_i)$  are iteratively adjusted to maximize  $P(O(x, y) | \lambda_i)$  (step 404). The iterations are terminated if the difference of the likelihood functions in two consecutive iterations is smaller than a threshold (step 405).

In a two person model in one embodiment,  $x_1$  is the only parameter that is iteratively adjusted for the estimation of the model. The computation of the likelihood function for a two person model is described in the following steps. The reference numerals within [brackets] correspond to like-numbered steps illustrated in FIG. 11:

[1101] the initial values of  $(x_0, x_1, x_2)$  are determined such that  $x_0$  is the  $x$  coordinate of the leftmost point of the foreground region,  $x_2$  is the  $x$  coordinate of the rightmost point of the foreground region and  $x_1 = (x_0 + x_2)/2$ .

[1102] the ellipse fitting process (step 402 in FIG. 4) is performed in each of the two vertical slots bounded by  $(x_0, x_1)$  and  $(x_1, x_2)$  pairs. The ellipse fitting algorithm will be described in more detail later with respect to FIG. 5.

[1103] for the ellipses found, the following parameters are computed (step 403 in FIG. 4):

5

10

$$S_{in,j} = \frac{\sum_{(x,y) \in R_{in,j}} f(x,y)}{\sum_{(x,y) \in R_{in,j}} f(x,y) + b(x,y)} \quad (4A)$$

15

$$S_{out,j} = \frac{\sum_{(x,y) \in R_{out,j}} b(x,y)}{\sum_{(x,y) \in R_{out,j}} f(x,y) + b(x,y)} \quad (4B)$$

20

[1104] reestimate the value of  $x_1$  according to the following formula:

25

$$x_1^{(k+1)} = x_1^{(k)} + \mu \cdot \left[ (S_{in,0} - S_{out,0}) - (S_{in,1} - S_{out,1}) \right] \quad (4C)$$

where  $\mu$  is a constant around 20.

[1105] compute  $P(O|\lambda_2)$  from Equation (2). If the difference between  $P(O|\lambda_2)$  for consecutive values of parameter  $x_1$  is smaller than a threshold, stop iterations. The parameters of the ellipses given by the ellipse fitting algorithm, performed in each slot bounded by  $(x_0, x_1)$  and  $(x_1, x_2)$ , will determine the location and size of the people heads in the foreground region. If the difference between  $P(O|\lambda_2)$  for consecutive values of parameter  $x_1$  is bigger than the same threshold, then go to step 1102.

35

## 6. The Iterative Ellipse Fitting Algorithm

In step 402, the head within a video image is detected by iteratively fitting an ellipse around the upper portion of the foreground region inside the area bounded by  $x_{j-1}, x_j$  (where  $j = 1, \dots, \hat{j}$ ). The objective in an ellipse fitting algorithm is to find the  $x_0, y_0, a$  and  $b$  parameters of the ellipse such that:

40

$$((x - x_0)/a)^2 + ((y - y_0)/b)^2 = 1 \quad (5)$$

A general prior art technique for fitting the ellipse around the detected blobs in step 402 (Fig 4) is the use of the Hough Transform, described by Chellappa et al. in "Human and Machine Recognition of Faces: A Survey", Proceedings of the IEEE, vol. 83, no. 5, pp. 705-740, May 1993. However, the computational complexity of the Hough Transform approach, as well as the need for a robust edge detection algorithm, make it ineffective for real-time applications.

A better alternative for fitting the ellipse in step 402 (FIG. 4) is an inexpensive recursive technique that reduces the search for the ellipse parameters from a four dimensional space  $x_0, y_0, a, b$  to a one dimensional space. The parameter space of the ellipse is reduced based on the following observations:

- The width of the ellipse at iteration  $k + 1$  is equal to the distance between the right most and left most point of the blob at the line corresponding to the current centroid position,  $y_0^{(k)}$  i.e.

55

$$a^{(k+1)} = f_1(y_0^{(k)}). \quad (6)$$

where function  $f_1$  is determined by the boundary of the objects resulting from the connected component analysis.

- The centroid of the ellipse is located on the so-called "vertical skeleton" of the blob representing the person. The vertical skeleton is computed by taking the middle point between the left-most and the right-most points for each line of the blob. The  $x_0^{(k+1)}$  coordinate of the centroid of the ellipse at iteration  $k+1$  is located on the vertical skeleton at the line  $y_0^{(k)}$  corresponding to the current centroid position. Hence  $x_0^{(k+1)}$  will be uniquely determined as a function of  $y_0^{(k)}$ .

$$x_0^{(k+1)} = f_2(y_0^{(k)}), \quad (7)$$

where function  $f_2$  is a function determined by the vertical blob skeleton.

The  $b$  parameter of the ellipse (the length) is generally very difficult to obtain with high accuracy due to the difficulties in finding the chin line. However, generally the length to width ratio of the ellipse can be considered constant, such as  $M$ . Then, from Equation (6) :

$$b^{(k+1)} = M \cdot a^{(k+1)} = M \cdot f_2(y_0^{(k)}) \quad (8)$$

From Equation (5) we write:

$$y_0^{(k+1)} = F(x_0^{(k+1)}, a^{(k+1)}, b^{(k+1)}). \quad (9)$$

Equations (6), (7), (8) and (9) lead to:

$$y_0^{(k+1)} = G(y_0^{(k)}), \quad (10)$$

which describes the iterative ellipse-fitting process algorithm of the present invention. Equation (10) indicates that we have reduced the four-dimensional problem of finding the ellipse parameters to an implicit equation with one unknown  $y_0$ .

With this in mind, the ellipse fitting process is illustrated in further detail in FIG. 5. In step 503 the edges and the vertical skeleton of the foreground regions in the area bordered by  $x_{i-1}, x_i$  are extracted. After the extraction of the skeletons of the foreground regions, the  $y_0$  parameter of the ellipse is iteratively computed.

In one embodiment, the initial  $y$  coordinate of the ellipse centroid,  $y_0^{(0)}$  is chosen close enough to the top of the object on the vertical skeleton in order for the algorithm to perform well for all types of sequences from head-and-shoulder to full-body sequence (step 504). Typically the initial value of  $y_0^{(0)}$  is selected according to the following expression:

$$y_0^{(0)} = y_t + 0.1 \cdot (y_t - y_b) \quad (11)$$

where  $y_t$  is the  $y$  coordinate of the highest point of the skeleton and  $y_b$  is the  $y$  coordinate of the lowest point of the skeleton. Given the initial point  $y_0^{(0)}$ , the ellipse fitting algorithm iterates through the following loop to estimate the ellipse parameters. The reference numerals in [brackets] refer to the steps illustrated in FIG. 12.

- [1201] compute parameter  $2a^{(k)}$  by measuring the distance between the left and the right edges of the blob.
- [1202] compute parameter  $b^{(k)}$  by measuring the  $y$  distance between  $y_0^{(k)}$  and the highest point of the skeleton.
- [1203] compute the error  $e(k)$  (in step 505).

$$e(k) = b^{(k)} - Ma^{(k)}. \quad (12)$$

In sum, the goal of the ellipse fitting algorithm described herein is to minimize this value, i.e. to find the ellipse that

best satisfies the condition  $b = Ma$ ,  $M = 1,4$ .

[1204] compute the new value  $y_0^{(k+1)}$  (step 506) using a linear estimate given by the following equation:

$$y_0^{(k+1)} = y_0^{(k)} + \mu e(k) \quad (12A)$$

[1205] if the distance between two consecutive centroids is smaller than a threshold, stop the iterations. When the iterations stop,  $x_0, y_0, a$  and  $b$  describe the four parameters of the ellipse.

Otherwise, go to step 1203.

The above iterations converge to the ellipse parameters for an ellipse type contour. From equation (1), the distance between the right most and left most point of the ellipse corresponding to  $y_0^{(k)}$  is determined by:

$$a^{(k)} = 2a\sqrt{1-((y_0^{(k)} - y_0)/Ma)^2} \quad (13)$$

and the distance between the top of the ellipse and  $y_0^{(k)}$  is determined by

$$b^{(k)} = y_0 + Ma - y_0^{(k)} \quad (14)$$

Hence, for  $\mu = 1$ , equation (1) becomes:

$$y_0^{(k+1)} - y_0 = Ma - Ma\sqrt{1-((y_0^{(k)} - y_0)/Ma)^2} \quad (15)$$

From the above equation it can be proved that

$$|y_0^{(k+1)} - y_0|^2 < |y_0^{(k)} - y_0|^2 \quad (16)$$

for any  $y_0^{(k)}$  for which  $|y_0^{(k)} - y_0| < Ma$ . This shows that the recurrence defined in equation (10) converges to  $y_0$ .

## 7. Eye Detection Process

The ellipses detected from stage 201, and as described previously, are potentially the region of support for human faces. After the detection of these regions, a more refined model for the face is required in order to determine which of the detected regions correspond to valid faces. The use of the eye detection process of stage 202, in conjunction with the head detection stage 201, improves the accuracy of the head model and removes regions corresponding to back views of faces or other regions that do not correspond to a face. Eye detection results can also be used to estimate the face pose and to determine the image containing the most frontal poses among a sequence of images. This result may then be used in recognition and classification systems.

The present invention may use an eye-detection algorithm based on both region size and geometrical measure filtering. The exclusive use of geometrical measures to detect the eyes inside a rectangular window around the ellipse centroid (eye band: W eye 1001 in Fig 10) may lead to problems in the analysis of non-frontal faces. In these cases, the hair regions inside the eye band generate small hair regions that are not connected to each other and that are in general close in size and intensity to the eye regions. Under the assumption of varying poses, the simple inspection of geometrical distances between regions and positions inside the eye band cannot indicate which regions correspond to the eyes. Hence, a more difficult approach based on region shape can be taken into account. However, in the present invention, a simple method may be implemented to discriminate eye and hair regions that perform with good results for a large number of video image sequences. In this approach, the small hair regions inside the eye band are removed by analyzing the region sizes in a larger window around the upper portion of the face (W face-up 1002 in Fig 10). Inside this window, the hair corresponds to the region of large size.

Stage 202 of FIG. 2 illustrates the steps of the eye detection approach that may be used according to the present invention. In step 221, the pixel intensities inside the face regions are compared to a threshold  $\theta$ , and pixels with intensities lower than  $\theta$  are extracted from the face region. In step 222, and as shown in FIG. 7A, the connectivity

analysis of the extracted pixels generates connected sets of pixels (e.g., pixels 701), i.e. sets of pixels that are adjacent or touching. Each of these connected sets of pixels 701 describe a low intensity region of the face.

In step 223, the pixel regions 701 resulting from steps 221-222 are filtered with respect to the region size. Regions having a small number of pixels due to camera noise or shadows are removed. Large regions generally cannot represent eyes, but instead correspond in general to hair. The size of the regions selected at this stage is in the interval  $[\theta_m, \theta_M]$  where  $\theta_m$  is the minimum and  $\theta_M$  is the maximum number of pixels allowed by our system to describe a valid eye region. Threshold values  $\theta_m, \theta_M$  are determined based on the size of the ellipse that characterizes the head region (the ellipse being generated iteratively in step 215). The end result of step 223 is an image 702, such as that shown in FIG. 7B.

In step 224, the remaining components within the image of FIG. 7B are filtered based on anthropological measures, such as the geometrical distances between eyes and the expected position of the eyes inside a rectangular window (eye band) centered in the ellipse centroid. The eye regions are determined by analyzing the minimum and maximum distance between the regions inside this band. The output 230 of step 224 is an image, such as shown in FIG. 7C, whereby the eyes 703 have been detected.

The present invention may be implemented on a variety of different video sequences from camera 110. FIGS. 8A, 8B, 8C and 8D depict the results obtained by operating the present invention in a sample laboratory environment, based upon the teachings above. FIGS. 8A-8D comprise four different scenarios generated to demonstrate the performances under different conditions such as non-frontal poses, multiple occluding people back views, and faces with glasses. In FIG. 8A, the face 812 of a single person 811 is detected, via ellipse 813. In this figure, the ellipse 813 is properly fitted around the face 812 and the eyes 814 are detected even though the person 811 is wearing optical glasses on his face 812.

FIG. 8B shows the back view of a single person 821 in the video scene. In this figure, the ellipse 823 is fitted around the head of the person 821, but no eye is detected, indicating the robustness of the eye detection stage 202 of the present invention.

FIGS. 8C and 8D show two scenarios in which two people 831A and 831B are present in the scene. In both figures the body of one person 831B is covering part of the body of the other person 831A. In both cases, ellipses 833A and 833B are positioned around the faces 832A and 832B, and eyes 834A and 834B are detected. In FIG. 8D, the face 832A of the person 831A in the back has a non-frontal position. Also due to different distances from the camera 110, the size of the two faces 832A and 832B are different. The faces 832A and 832B of both persons 831A and 831B are detected indicating the robustness of the system to variations in parameters such as size and position of the faces 832A and 832B.

Although the present invention has been described with particular reference to certain preferred embodiments thereof, variations and modifications of the present invention can be effected within the spirit and scope of the following claims.

## Claims

1. A system for processing a video image comprising pixels representing a foreground including one or more human faces, the system comprising;

component analysis means (212,213) to process the pixels of the image to identify a region of connected components in the foreground of the image,

ellipse fitting means (503,504,505,506,507) to perform an iterative ellipse fitting algorithm to fit one or more ellipses to the connected components in the identified region,

means (301) to provide a model of borders for one or more separate individual faces in the identified region, probability computing means (403) to perform a computation of the probability of the model based on the ellipse or ellipses fitted in the identified region, and means (404,405) to iteratively adjust the model to maximise the probability computation.

2. A system as claimed in claim 1, further comprising means (221) to identify sub-regions within the identified region that are below a selected low intensity threshold, means (223) to filter out those of the sub-regions that are below a selected small size or above a selected large size, and

means (224) to filter the remaining sub-regions based on anthropological measures to derive co-ordinates representing eyes.

3. A system as claimed in claim 1 or 2, in which the component analysis means (212,213) includes background subtraction and thresholding means (212) to subtract pixels representing background in the video image.

5

- 4. A system as claimed in claim 1, 2 or 3, in which the ellipse fitting means (503,504,505,506,507) include means (503) to detect edges and vertical skeleton lines in the identified region, means (504) to form an initial centroid estimation, means (505) to compute the error in the centroid estimation, means (506) to compute a new centroid estimation and means (507) to stop the iteration when the distance between two centroid estimates is smaller than a predetermined threshold.
- 10
- 5. A system as claimed in claim 1, 2, 3 or 4, in which the means (301) to provide a model of borders for one or more separate individual faces is effective to provide a selection of such models, each such model comprising a different selection of vertical borders.
- 15
- 6. A system as claimed in claim 5, in which the probability computing means (403) are operable to compute the probability of each of a plurality of models, means being provided to select the model for which the highest probability is computed.
- 20
- 7. A system as claimed in any one of the preceding claims, further comprising a video camera (110) to generate the said video image and storage means (150) to store the video image.
- 25
- 8. A system as claimed in any one of the preceding claims, further comprising recognition and classification means to process the model to detect a face within the video image.

25

30

35

40

45

50

55

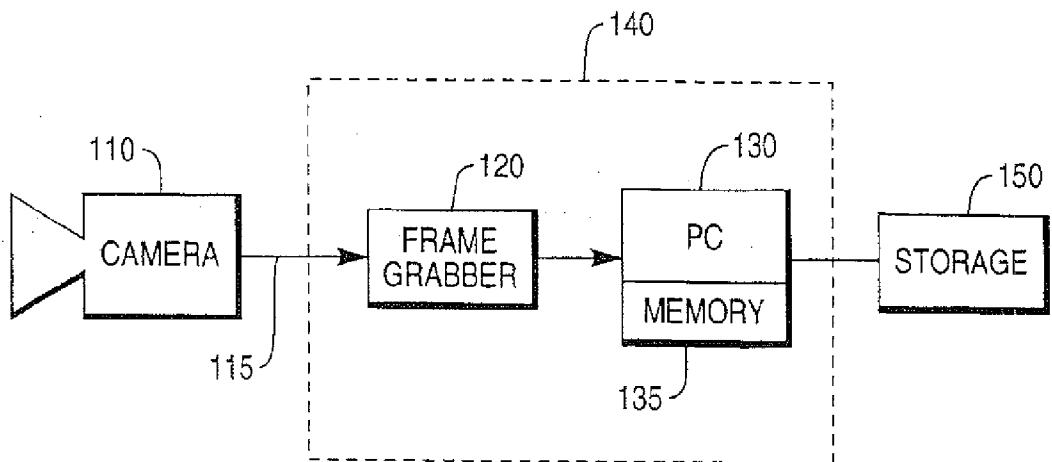
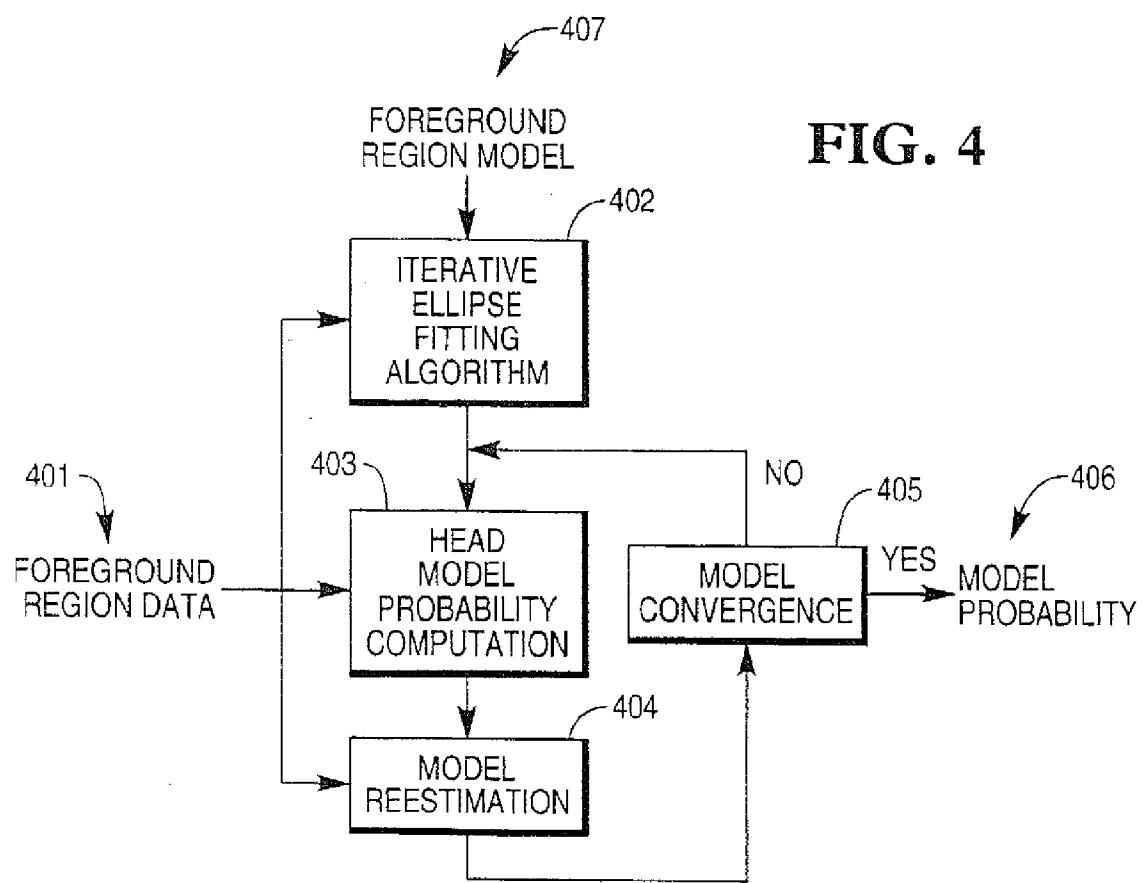
**FIG. 1****FIG. 4**

FIG. 2

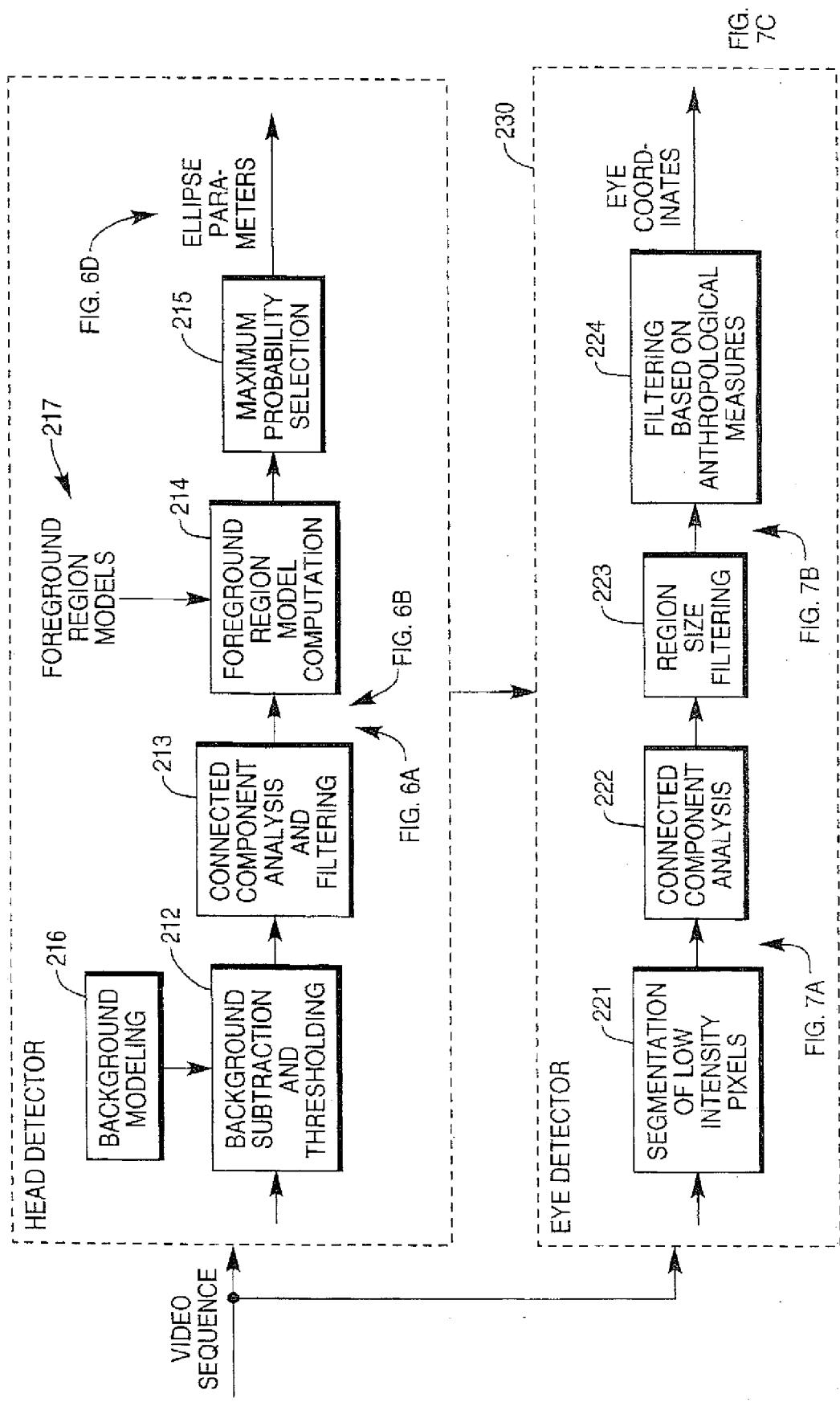
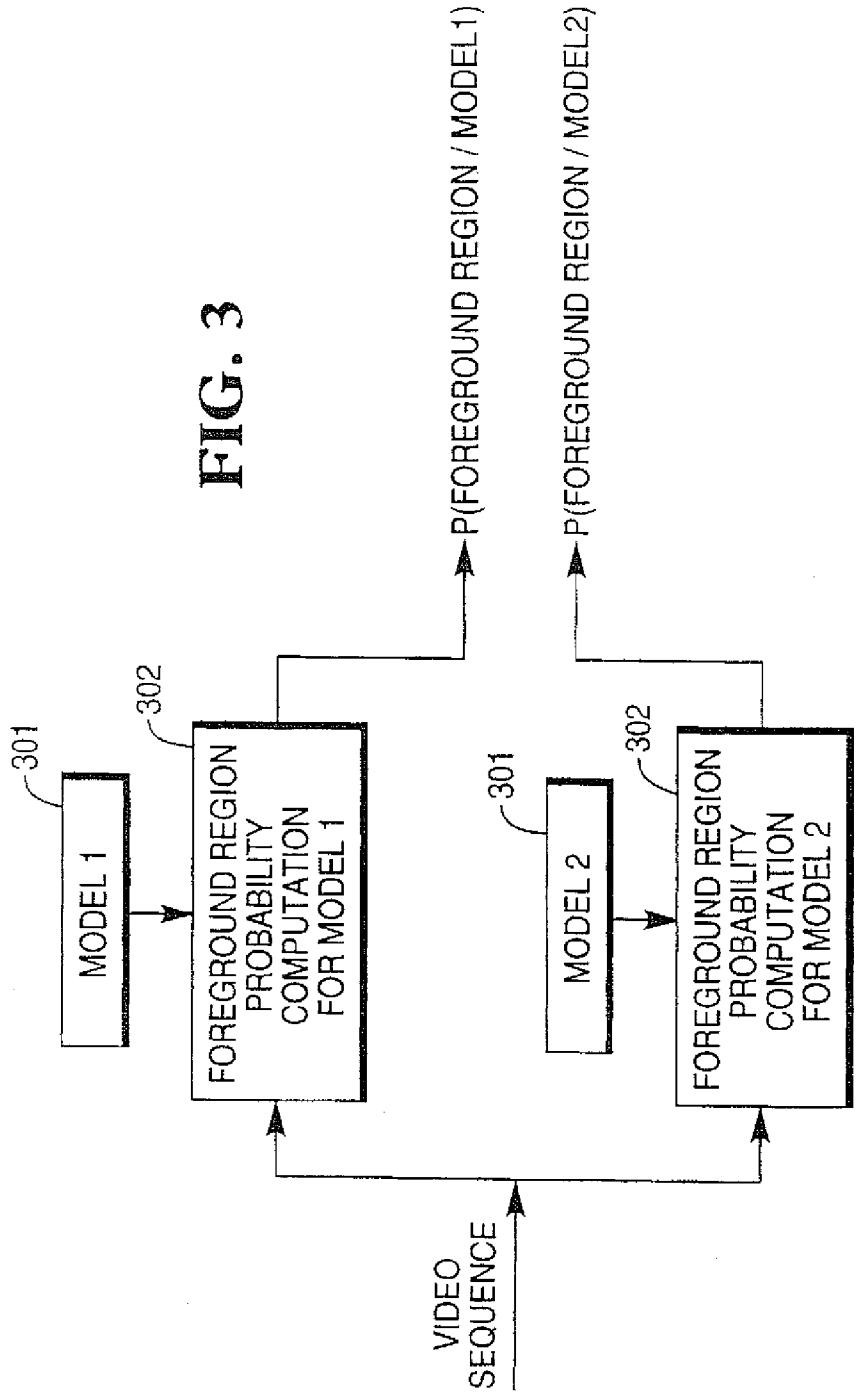
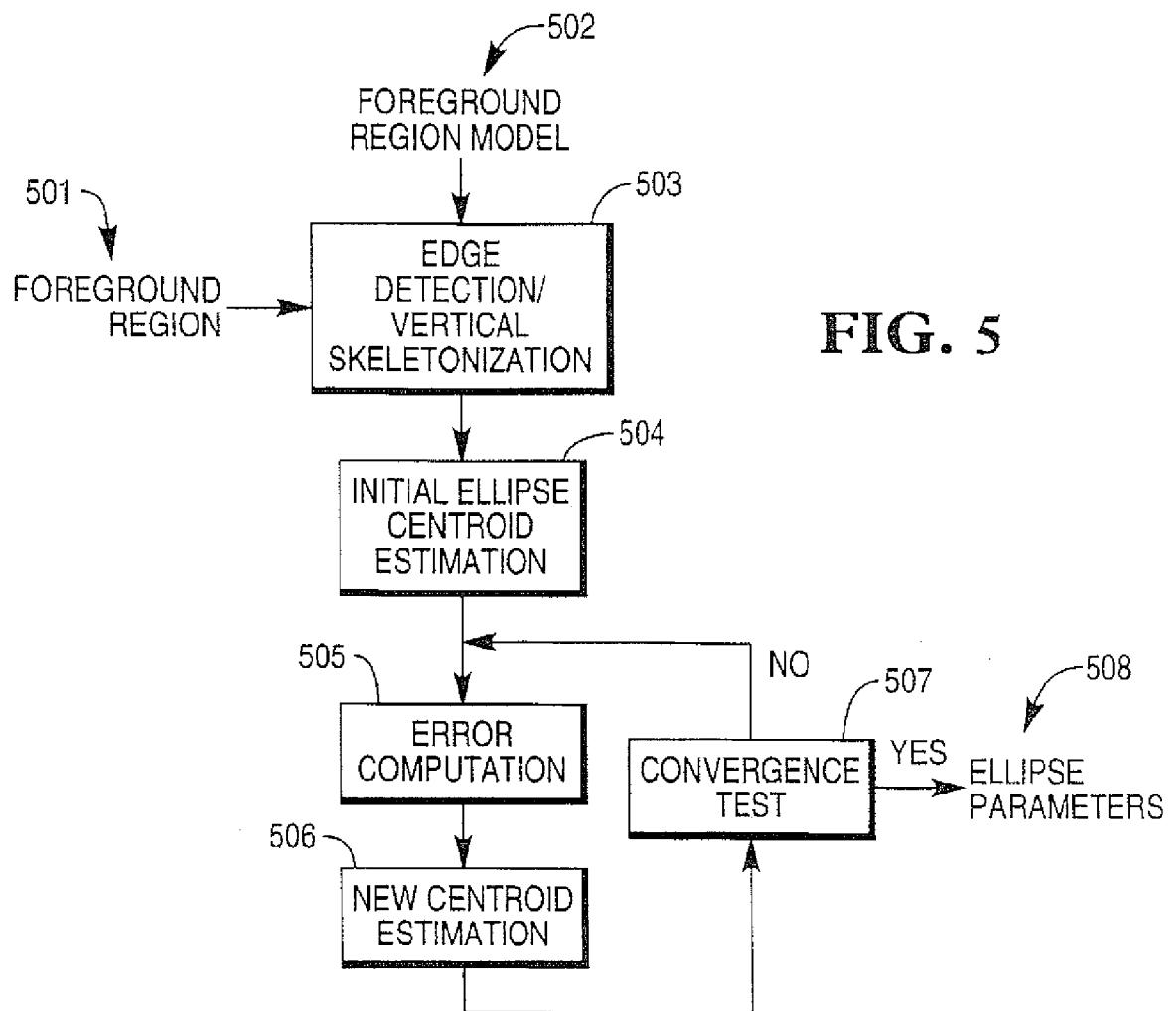
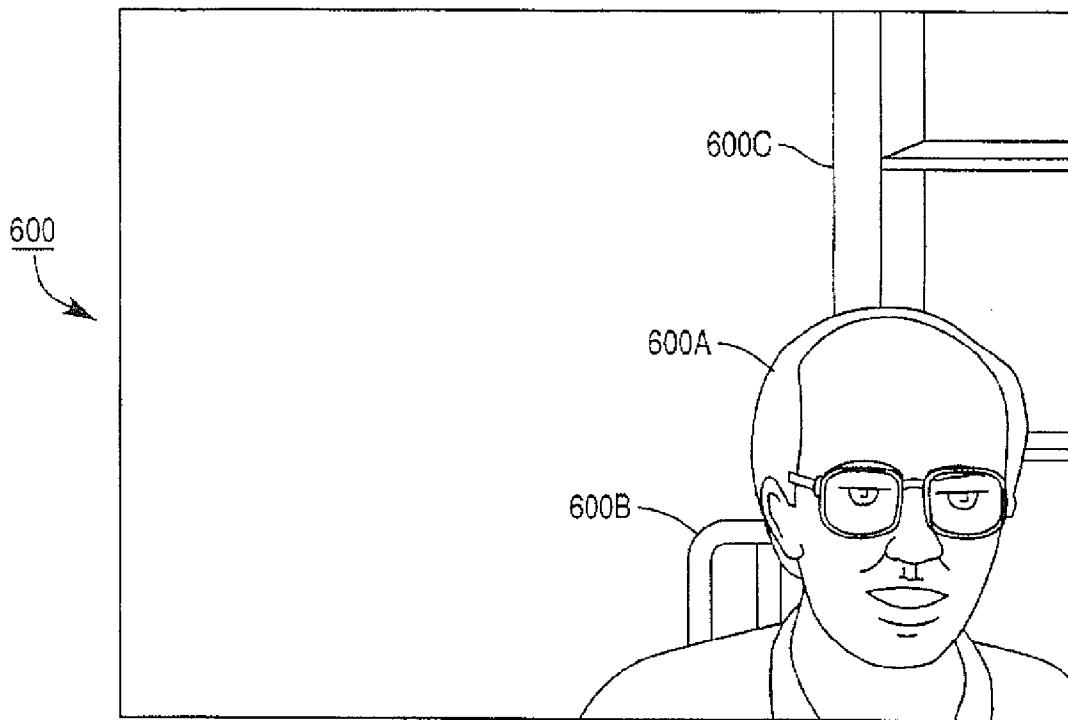


FIG. 3

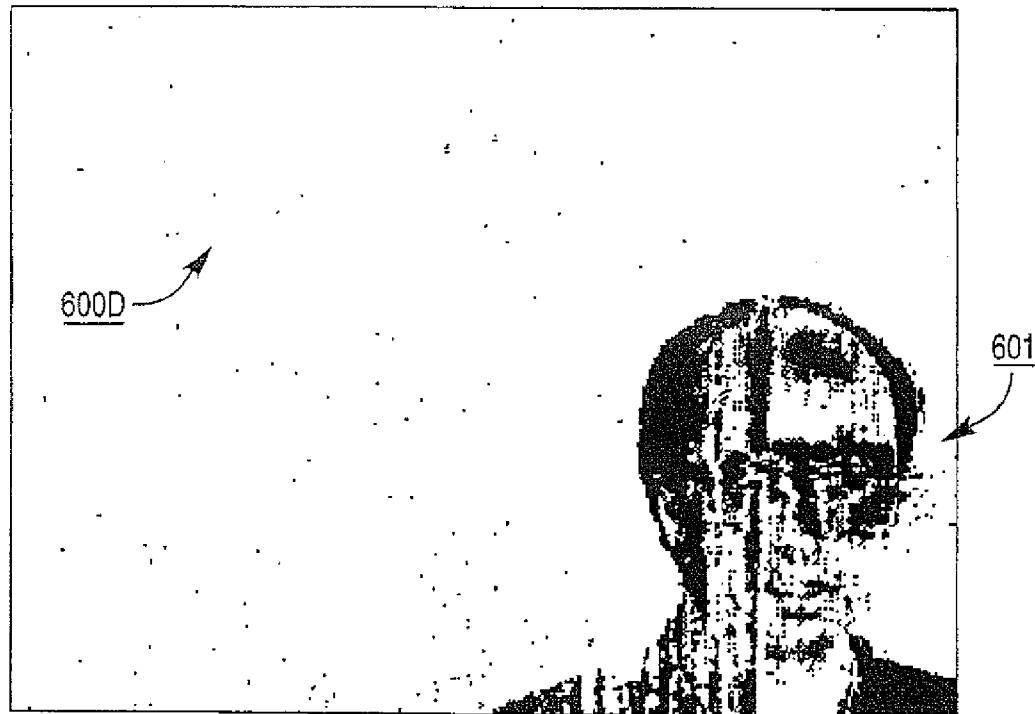




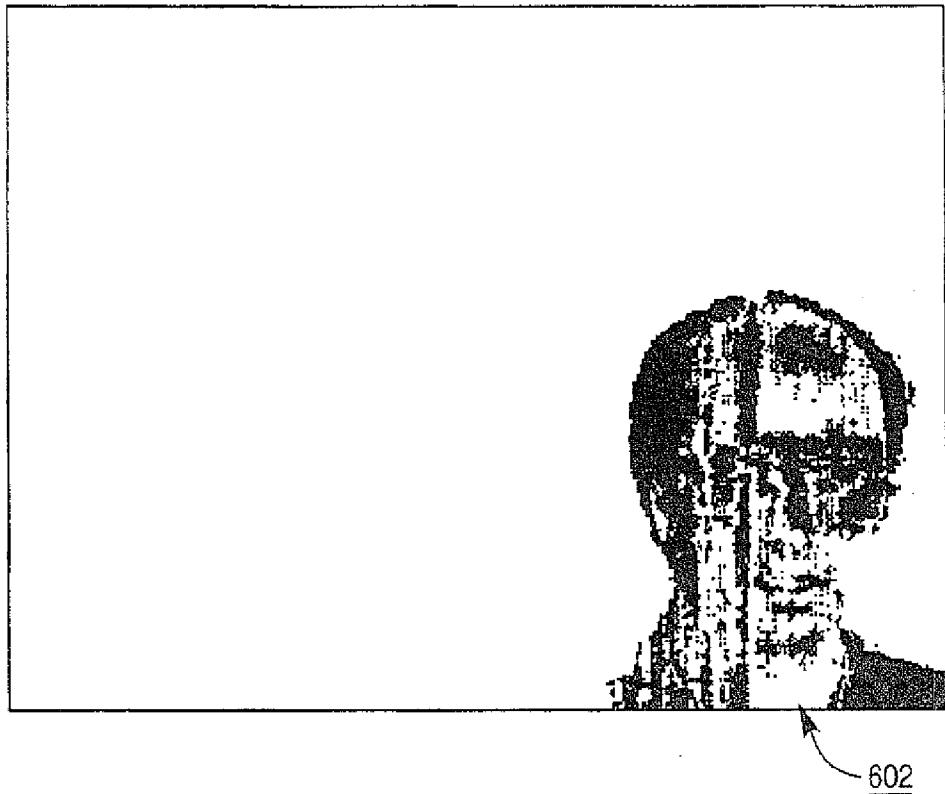
**FIG. 6A**



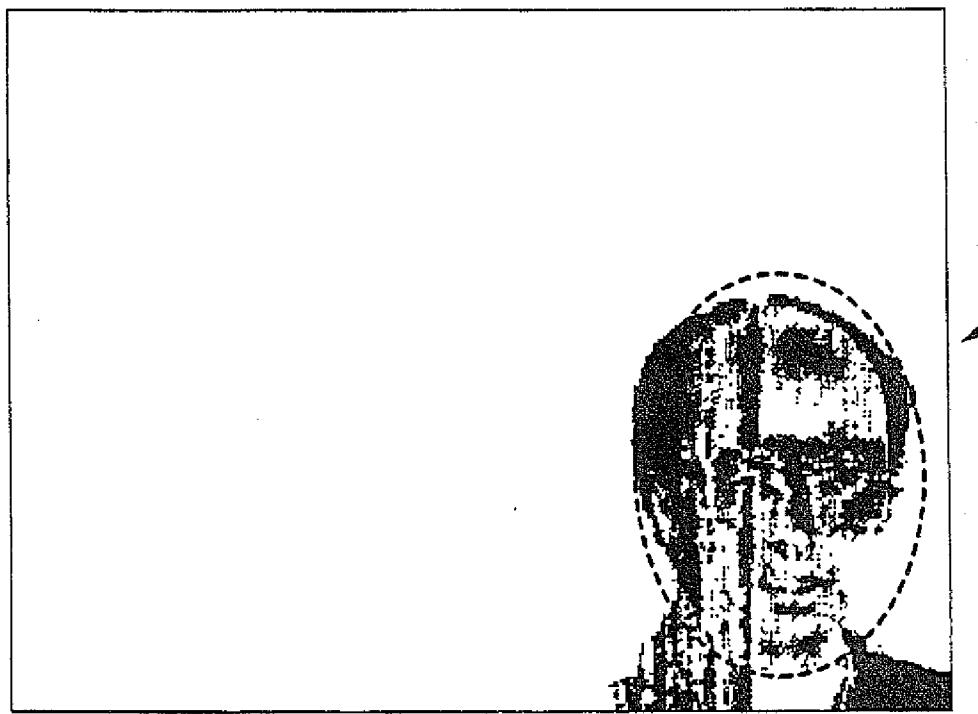
**FIG. 6B**



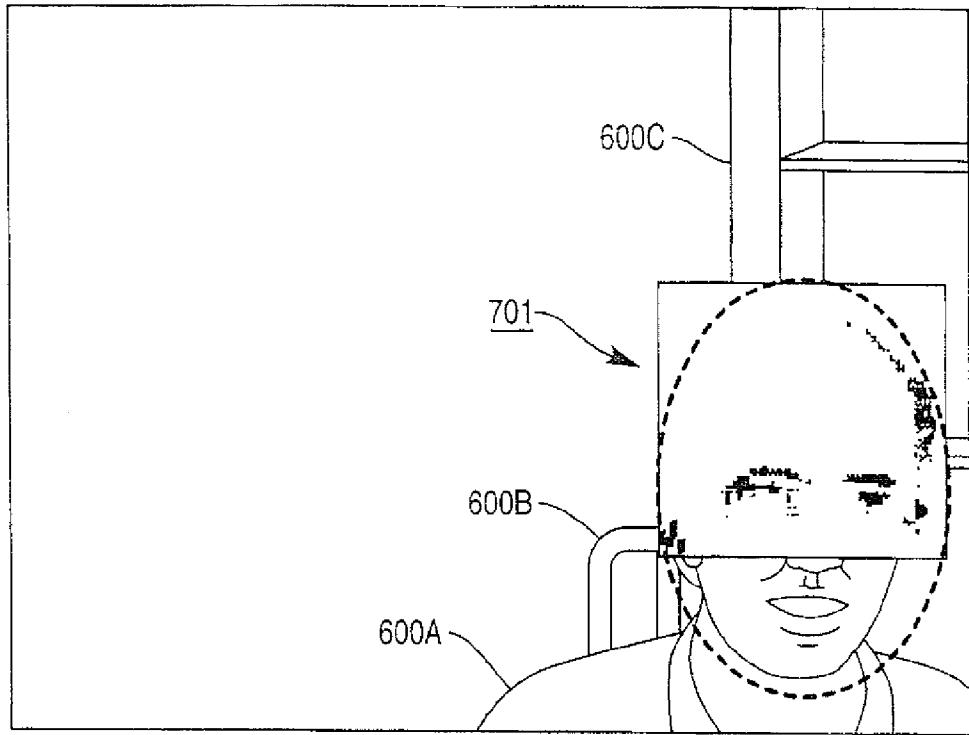
**FIG. 6C**



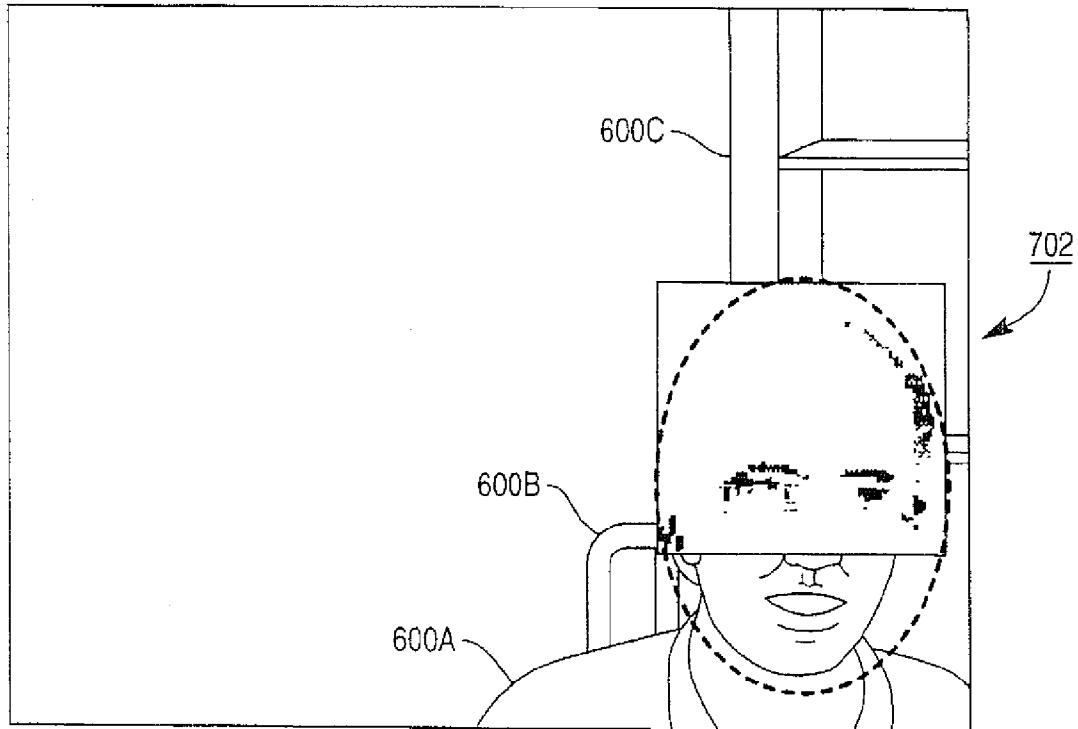
**FIG. 6D**



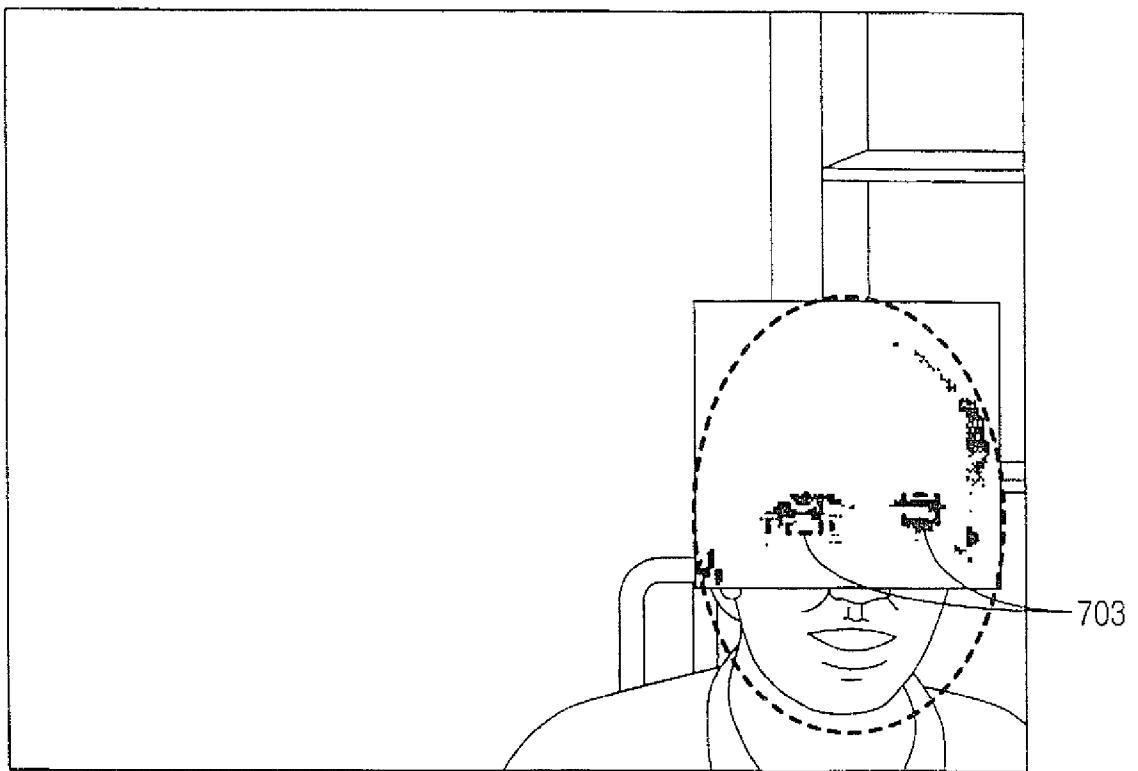
**FIG. 7A**



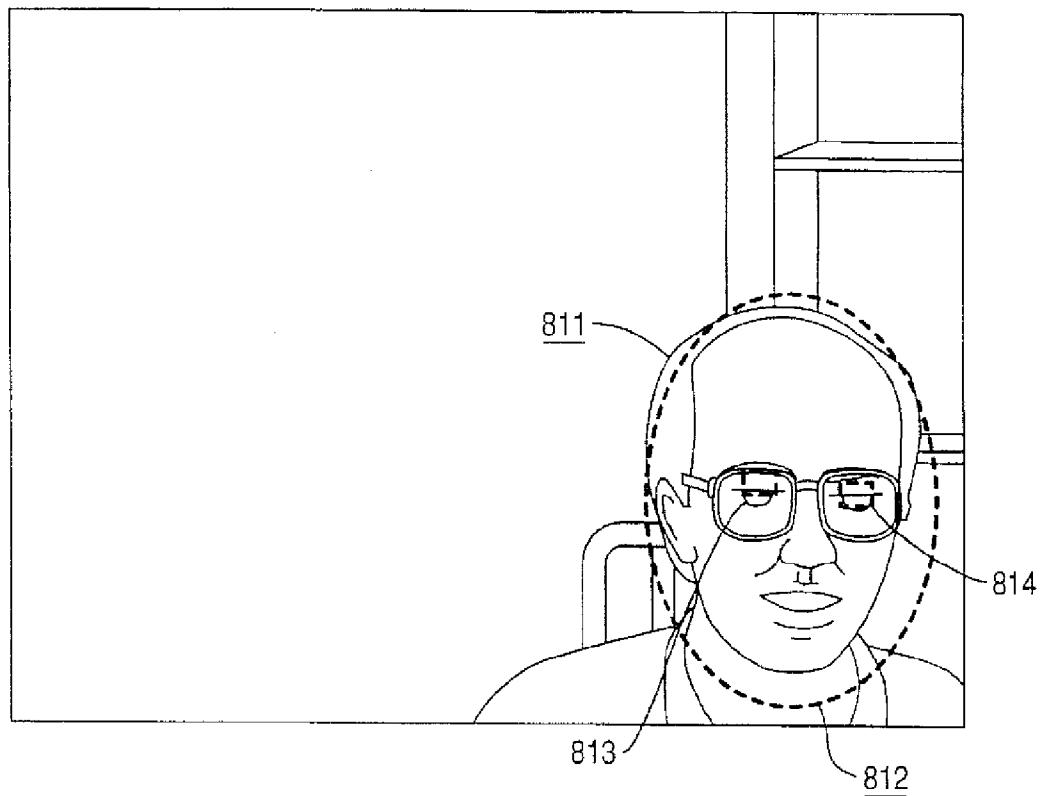
**FIG. 7B**



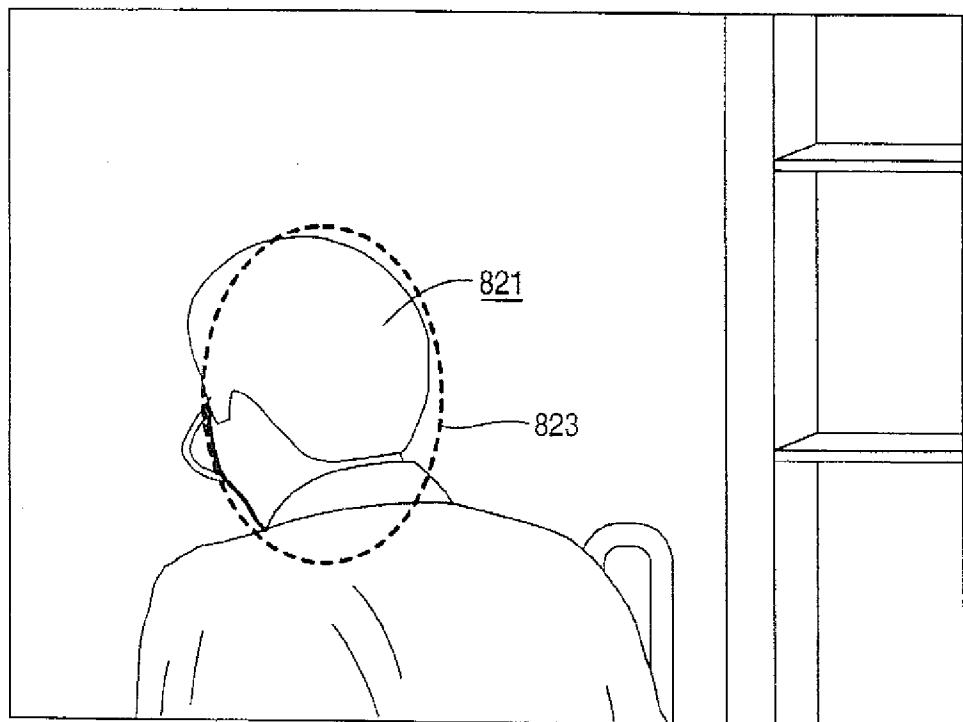
**FIG. 7C**



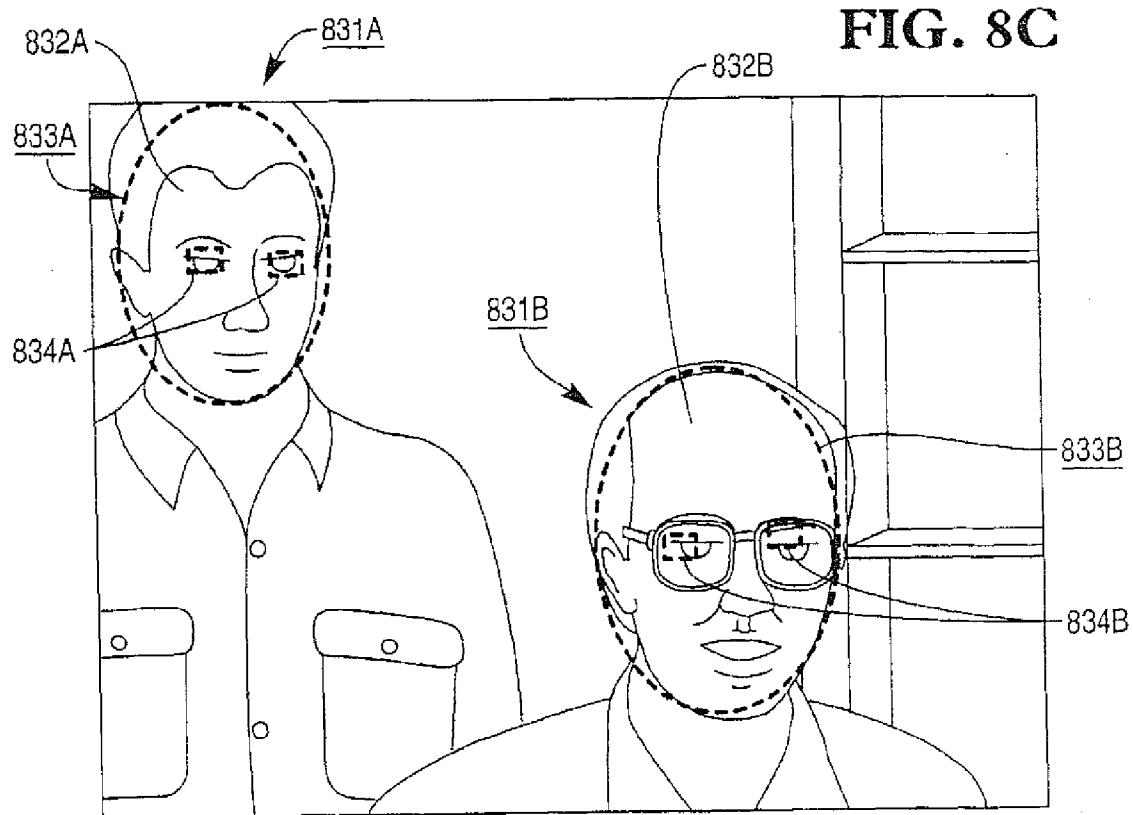
**FIG. 8A**



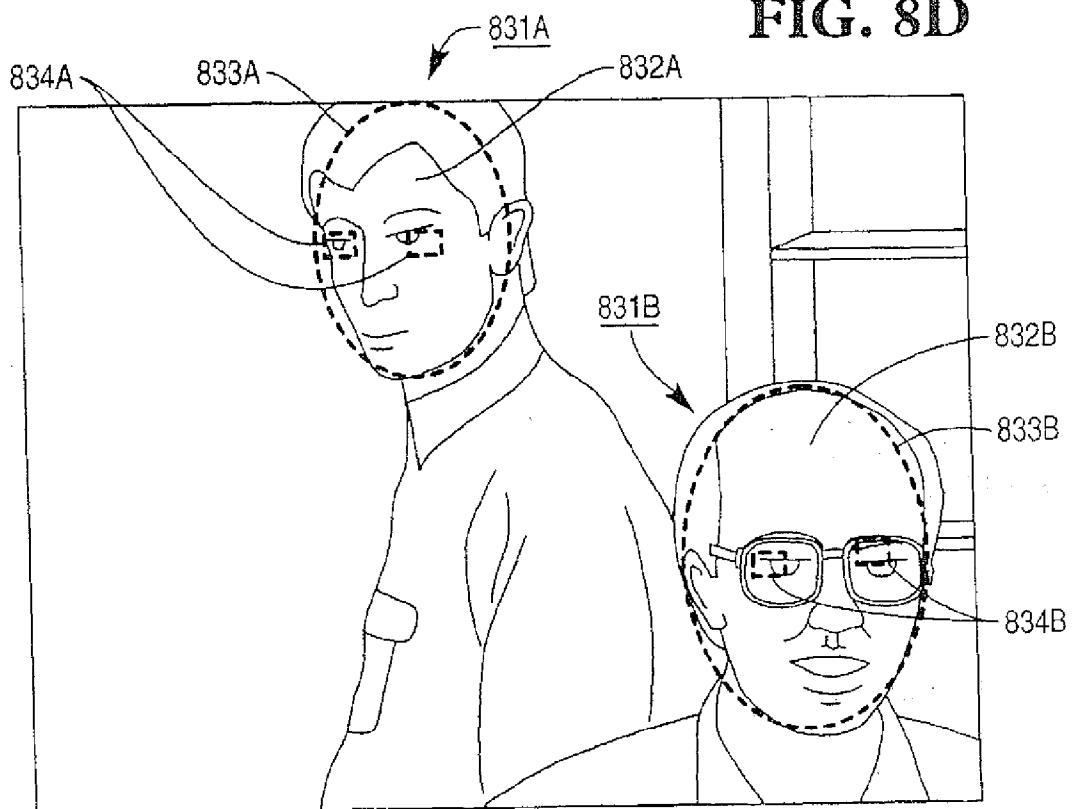
**FIG. 8B**



**FIG. 8C**

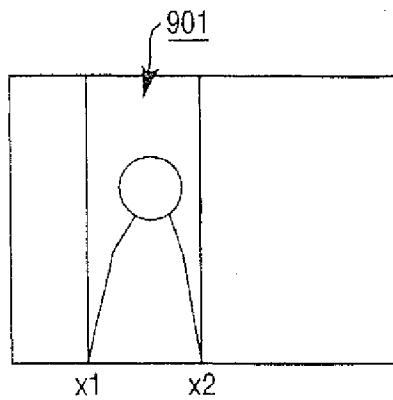


**FIG. 8D**

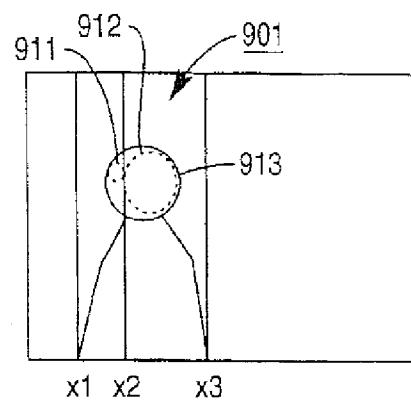


**FIG. 9**

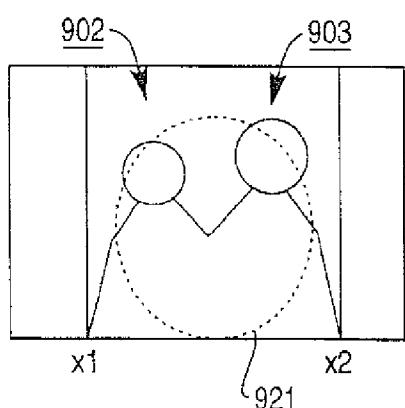
**FIG. 9A**



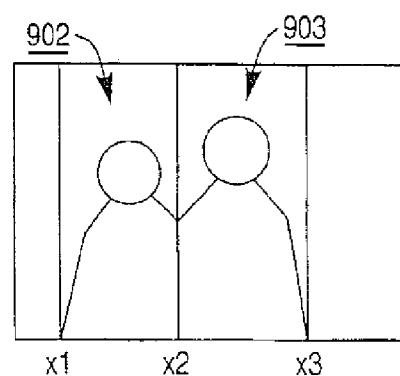
**FIG. 9B**



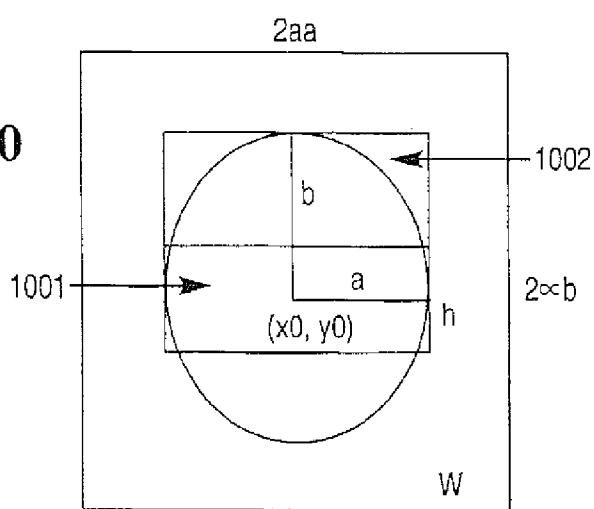
**FIG. 9C**



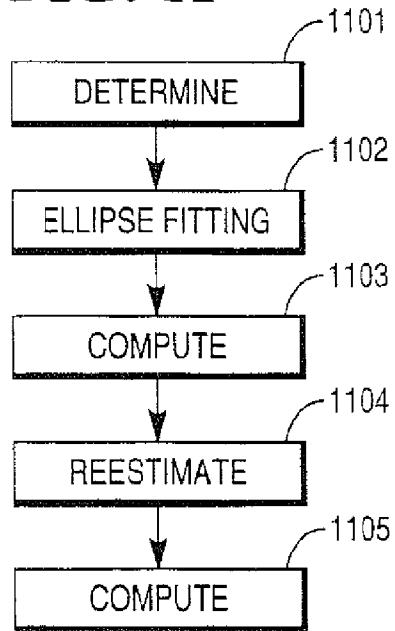
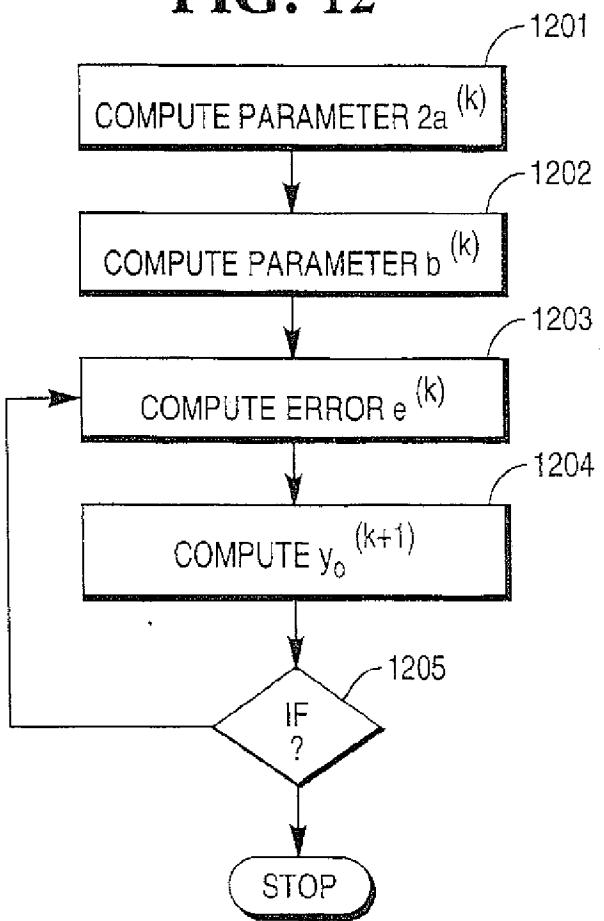
**FIG. 9D**



**FIG. 10**



ELLIPSE MODEL =  $(x_0, y_0, a, b)$ ,  $b = Ma$ ,  $M = 1.4$   
 $h = b/6$

**FIG. 11****FIG. 12**



(19)

Europäisches Patentamt

European Patent Office

Office européen des brevets



(11)

EP 0 844 582 A3

(12)

## EUROPEAN PATENT APPLICATION

(88) Date of publication A3:  
26.05.1999 Bulletin 1999/21

(51) Int Cl<sup>6</sup>: G06K 9/00

(43) Date of publication A2:  
27.05.1998 Bulletin 1998/22

(21) Application number: 97309444.4

(22) Date of filing: 24.11.1997

(84) Designated Contracting States:  
AT BE CH DE DK ES FI FR GB GR IE IT LI LU MC  
NL PT SE

Designated Extension States:  
AL LT LV MK RO SI

(30) Priority: 26.11.1996 US 31816 P  
21.05.1997 US 859902

(71) Applicant: NCR INTERNATIONAL INC.  
Dayton, Ohio 45479 (US)

(72) Inventors:

- Khosravi, Mehdi  
Roswell, Georgia 30075 (US)
- Hayes, Monson Henry, III  
Marietta, Georgia 30068 (US)
- Nefian, Ara Victor  
Atlanta, Georgia 30319 (US)

(74) Representative: Cleary, Fidelma et al  
International IP Department  
NCR Limited  
206 Marylebone Road  
London NW1 6LY (GB)

## (54) System and method for detecting a human face

(57) The present invention relates to a system for the processing of video images which include human faces. The invention is applicable to a system in which the images are generated by a video camera and stored in a storage means ready to be processed.

The system for processing the images include component analysis means (212,213) to analyse the pixels of the image to identify a region of connected components in the foreground of the image. An ellipse fitting means (503,504,505,506,507) performs an iterative ellipse fitting algorithm to fit one or more vertical ellipses

to the connected components in the identified region, each ellipse representing a possible human face. In order to distinguish between occluded human figures, a plurality of possible models of borders are presented to separate individual faces in the identified region. Probability computing means (403) perform a computation of the probability of each model based on the ellipse or ellipses fitted in the identified region. The parameters of each model are iteratively adjusted to maximise the probability computation for that model and a selection is made of the model having the highest probability.

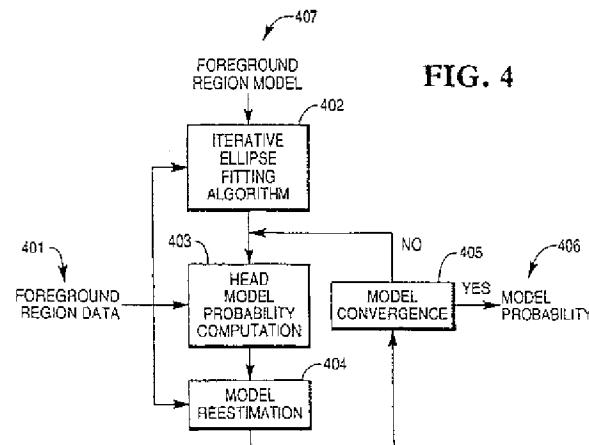


FIG. 4



European Patent  
Office

## EUROPEAN SEARCH REPORT

Application Number

EP 97 30 9444

DOCUMENTS CONSIDERED TO BE RELEVANT									
Category	Citation of document with indication, where appropriate, of relevant passages	Relevant to claim	CLASSIFICATION OF THE APPLICATION (Int.Cl.6)						
X	<p>SABER E ET AL: "Face detection and facial feature extraction using color, shape and symmetry-based cost functions" PROCEEDINGS OF THE 13TH INTERNATIONAL CONFERENCE ON PATTERN RECOGNITION, PROCEEDINGS OF 13TH INTERNATIONAL CONFERENCE ON PATTERN RECOGNITION, VIENNA, AUSTRIA, 25-29 AUG. 1996, pages 654-658 vol.3, XP002097369 ISBN 0-8186-7282-X, 1996, Los Alamitos, CA, USA, IEEE Comput. Soc. Press, USA * paragraph 2.2 - paragraph 2.6; figure 1 *</p> <p>-----</p> <p>SOBOTTKA K ET AL: "FACE LOCALIZATION AND FACIAL FEATURE EXTRACTION BASED ON SHAPE AND COLOR INFORMATION" PROCEEDINGS OF THE INTERNATIONAL CONFERENCE ON IMAGE PROCESSING (IC, LAUSANNE, SEPT. 16 - 19, 1996, vol. 3, 16 September 1996, pages 483-486, XP000704075 INSTITUTE OF ELECTRICAL AND ELECTRONICS ENGINEERS * paragraph 2.1 - paragraph 2.2 *</p> <p>-----</p> <p>"METHOD FOR EXTRACTING FACIAL FEATURES BY USING COLOR INFORMATION" IBM TECHNICAL DISCLOSURE BULLETIN, vol. 38, no. 10, 1 October 1995, pages 163-165, XP000540455 * the whole document *</p> <p>-----</p>	1-4,7,8	G06K9/00						
			<table border="1"> <tr> <td>TECHNICAL FIELDS SEARCHED (Int.Cl.6)</td> </tr> <tr> <td>G06K</td> </tr> </table>	TECHNICAL FIELDS SEARCHED (Int.Cl.6)	G06K				
TECHNICAL FIELDS SEARCHED (Int.Cl.6)									
G06K									
<p>The present search report has been drawn up for all claims</p> <table border="1"> <tr> <td>Place of search</td> <td>Date of completion of the search</td> <td>Examiner</td> </tr> <tr> <td>THE HAGUE</td> <td>22 March 1999</td> <td>Sonius, M</td> </tr> </table> <p>CATEGORY OF CITED DOCUMENTS</p> <p>X : particularly relevant if taken alone Y : particularly relevant if combined with another document of the same category A : technological background O : non-written disclosure P : intermediate document</p> <p>T : theory or principle underlying the invention E : earlier patent document, but published on, or after the filing date D : document cited in the application L : document cited for other reasons &amp; : member of the same patent family, corresponding document</p>				Place of search	Date of completion of the search	Examiner	THE HAGUE	22 March 1999	Sonius, M
Place of search	Date of completion of the search	Examiner							
THE HAGUE	22 March 1999	Sonius, M							